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**The Adaptive Decision-Maker:
Effort and Accuracy in Choice**

John W. Payne¹, James R. Bettman¹
and Eric J. Johnson²

January 1989

Center for Decision Studies

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19. ABSTRACT (Continue on reverse if necessary and identify by block number) Research has shown that the strategies people use to evaluate and choose among a set of multiattribute alternatives are highly sensitive to a variety of task and context variables. This chapter reviews a program of research concerned with better understanding how decision making behavior is contingent upon properties of the decision task. The perspective adopted is that strategy selection is a function of both costs, primarily the effort required to use a decision rule, and benefits, primarily the ability of a strategy to select the best alternative. A series of experiments involving both Monte-Carlo simulation and process-tracing techniques is reported that support the effort-accuracy framework. Unresolved issues of learning, bottom-up as well as top-down processing, and the role of incentives in strategy selection are then discussed. Finally, an implication of adaptive decision behavior for improving decisions by designing information displays which make effective processing easier is outlined. (KF) ←					
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In his dissertation research, Hillel Einhorn examined a question that is central to behavioral decision research and of substantial applied interest: How do people evaluate and choose among a set of multiattribute alternatives (Einhorn, 1970; Einhorn, 1971)? Einhorn concluded that no single model such as additive utility was likely to be an adequate general representation of evaluative decision making. He proposed that conditions should be specified under which various models apply as representations of human decision making. The work described in this chapter follows Einhorn's suggestion and considers why decision makers, given a particular decision task, select one particular decision strategy instead of others.

Contingent strategy selection reflects the fascinating ability of individuals to adapt to a wide variety of environmental conditions. The issue of strategy selection also reflects a growing concern in cognitive psychology with the regulation of cognition, or "metacognition" (Brown, Bransford, Ferrara, & Campioni, 1983). The research program described in this chapter emphasizes the adaptivity of human decision behavior to task demands and the cognitive control question of how one decides how to decide.

Deciding How To Decide

The most frequently advocated approach to explaining strategy selection is to assume that strategies have differing advantages and disadvantages and to hypothesize that an individual selects the strategy that is "best" for the task (Beach & Mitchell, 1978). Several factors, such as the chance of making an error, (Thorngate, 1980), avoidance of conflict (Hogarth, 1987), and justifiability (Tversky, 1972), can affect decision makers' perceptions of the appropriateness of a strategy for a particular task and hence can affect strategy selection. However, our research has focused on the role played in strategy choice by the



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cognitive effort (mental resources) required to execute a strategy in a specific task environment.

The idea that decision making is influenced by considerations of cognitive effort is an old one (e.g., Simon, 1955; Marschak, 1968). It seems obvious, for example, that different strategies require different amounts of computational effort. Expected utility maximization, for instance, requires a person to process all relevant problem information and to trade off values and beliefs. The lexicographic choice rule (Tversky, 1969), on the other hand, chooses the alternative which is best on the most important attribute, ignoring much of the potentially relevant problem information.

At a more precise level of analysis, however, a comparison among decision strategies in terms of cognitive effort is more difficult. In part this is because decision strategies proposed in the literature have varied widely in terms of their formal expression. Some have been proposed as formal mathematical models (e.g., elimination-by-aspects, Tversky, 1972), and others as verbal process descriptions (e.g., the majority of confirming dimensions rule, Russo & Doshier, 1983). The research described here developed a language that could be used to express a diverse set of decision strategies in terms of a common set of elementary information processes. That language allows strategy selection to be investigated at a detailed information processing level rather than at a more general level of analysis, such as comparisons of analytic vs. nonanalytic (Beach & Mitchell, 1978) or analytic vs. intuitive strategies (Hammond, 1986). One can examine, for instance, how cognitive effort is affected by both the amount of information to be processed and the specific mix of elementary information processes used.

In addition to cognitive effort, we have been concerned with how the use of simplified decision rules affects the accuracy of decisions. For example, a

simple equal weighting strategy can closely approximate the accuracy of an optimal weighting rule in some task environments (Einhorn & Hogarth, 1975).

The rest of this chapter is organized as follows: First, studies which test and elaborate the implications of an effort/accuracy framework for strategy selection are briefly reviewed. The studies include (1) Monte-Carlo simulations of how the effort and accuracy of different strategies might vary across task environments; (2) An empirical test of various models of subjects' effort using different decision strategies in different choice environments; and (3) Experiments that examine whether the actual decision behaviors exhibited by subjects across different task environments are consistent with the efficient processing patterns identified by the simulation. Some unresolved issues relating to the effort/accuracy framework are then considered, such as the extent to which strategies may not be selected as much as "constructed" throughout the decision process. Such "construction" may allow individuals to notice and exploit structure in the choice set in ways that reduce effort (Bettman, 1979). Finally, some implications of our research for decision aiding are described.

Effort, Accuracy, and Choice Environments

As typically formulated, decision problems consist of three basic components: (1) The alternatives available to the decision maker; (2) Events or contingencies that relate actions to outcomes, as well as their associated probabilities; and (3) The values associated with the outcomes. These informational elements, along with a goal statement (such as "choose the preferred alternative"), represent the task environment presented to a decision maker. The decision maker's internal representation of this task environment is the individual's problem space, containing the solution (i.e., the preferred alternative) which must be identified (Newell & Simon, 1972). Generally,

decision tasks become more difficult with more alternatives, multiple contingencies, and multiple conflicting dimensions of value.

Much research supports Einhorn's suggestion (1970, 1971) that an individual will utilize a number of different information processing strategies to solve decision tasks (Abelson & Levi, 1985). Sometimes the strategies involve an exhaustive use of the available information in a form of compensatory processing. However, often the strategies used are heuristics that simplify search through the problem space either by disregarding some problem information or simplifying the processing done on particular elements of the problem. Examples of the latter are within-attribute comparison as opposed to the combining of information across attributes (Russo & Doshier, 1983). Alternative heuristics such as elimination-by-aspects (EBA), satisficing (SAT), lexicographic (LEX), and equal weighting (EQW) represent different simplification strategies for search through the problem space. For example, the equal weighting rule reduces processing by ignoring any differential weights for the decision outcomes while still examining the values for all outcomes. The lexicographic rule, on the other hand, uses the weights to limit search to one or a few of the most important attributes and simplifies processing by only using comparisons of one outcome value to another. More generally, people seem to react to the discrepancy between information processing demands and information processing capacity in decision making by (1) selectively processing a subset of the available information and/or (2) selectively applying operations to that information that are easier to perform.

The use of heuristics that save effort can also lead to serious decision errors (Tversky, 1969). However, some cognitive simplifications can both save effort and maintain reasonably high levels of accuracy in a given task environment (Einhorn & Hogarth, 1975). This point is crucial; we do not believe that heuristics and biases should be viewed as synonymous. Rather, we argue that

the use of heuristics often represents intelligent, if not optimal, decision making. Given this perspective, characterizing the effort required to use various heuristics and the accuracy of those heuristics in various task environments is essential. In the next section, we report Monte-Carlo simulation experiments that provide estimates of accuracy and effort for several heuristics in different decision task environments. Decision makers can potentially use such estimates to both save effort and maintain accuracy by selecting different heuristics for different task environments. In later sections, we examine whether decision makers in fact adapt to different tasks in ways that the simulations suggest are relatively efficient (i.e., that maintain accuracy with savings in effort).

Monte-Carlo Simulations of Effort and Accuracy in Choice

The two main purposes of the simulation studies were (1) To characterize the effort and accuracy of various strategies in different decision environments; and (2) To develop insights into how processing *might* change if efficient effort/accuracy tradeoffs were desired in selecting decision strategies. The simulations provide a "task analysis" of the problem of strategy selection in decision making. Additional details on the simulations can be found in Johnson and Payne (1985) and Payne, Bettman, and Johnson (1988).

Measuring Strategy Effort

Building on ideas of Newell and Simon (1972), ten decision strategies were decomposed into elementary information processes (EIPs). The set of strategies included weighted additive (WADD), elimination-by-aspects (EBA), equal weight (EQW), lexicographic (LEX), majority of confirming dimensions (MCD), satisficing (SAT), lexicographic semi-order (LEXSEMI), two combined strategies, and a random choice rule. Each decision strategy was viewed as a specific sequence of EIPs, such as reading the values of two alternatives on an attribute, comparing them,

and so forth. The set of EIPs used in the simulations included operators to (1) Read an alternative's value on an attribute into working memory; (2) Compare two alternatives on an attribute; (3) Add the values of two attributes in working memory; (4) Calculate the size of the Difference of two alternatives for an attribute; (5) Weight one value by another (Product); (6) Eliminate an alternative from consideration; (7) Move to the next element of the task environment; and (8) Choose the preferred alternative and end the process.

A count of the total number of EIPs used by a strategy to reach a decision in a particular choice environment provides a straightforward measure of the effort associated with the use of that decision strategy in that environment.¹ Several areas of cognitive research use EIP counts to measure processing load (e.g., Card, Moran, & Newell, 1983).

To illustrate how EIP counts of effort would be determined, consider the set of EIPs given above and a simple decision problem involving two options (A and B), two events with probabilities (weights), and two payoff values per option (one payoff for each of the two possible outcomes). For an elimination-by-aspects rule, the process might proceed as follows: First, the decision maker finds the most probable outcome (most important attribute; throughout this paper we use the terms outcome and attribute interchangeably). This involves reading the two probability values and comparing the two values to determine which is larger (2 Reads and 1 Compare). Next, the decision maker might acquire an explicit cutoff value and then compare the payoff values on the most probable outcome for each option against that cutoff value. If the first option (A) failed the cutoff and the second option (B) passed the cutoff, then a choice of B would be made. This process of comparing options to the cutoff involves 3 Reads, 2 Comparisons, 1 Elimination, and 1 Choice. Thus, the entire decision process

consists of 5 Reads, 3 Compares, 1 Elimination, and 1 Choice, for a total EIP Count of 10.

In contrast, if the weighted adding rule were used on the same size decision problem (2 options, 2 events, and 4 payoff values), one might proceed as follows: First the probability of event 1 and the payoff of option A given event 1 would be acquired (2 Reads). Next, the payoff would be multiplied by the probability (1 Product). The process would be repeated for the next probability and payoff and the two products would be added, for a total of 4 Reads, 2 Products, and 1 Addition. The same process would be repeated for option B. Finally, the overall values for A and B would be compared (1 Compare) and the option with the largest value chosen (1 Choice). The total EIP count would be 16 (8 Reads, 4 Products, 2 Additions, 1 Compare, and 1 Choice).

A particular set of EIPs, like the one given above, requires a theoretical judgment regarding the appropriate level of decomposition. For instance, the product operator might itself be decomposed into more elementary processes. We hypothesized, however, that a reasonable approximation of the cognitive effort associated with a strategy could be obtained from the above level of decomposition. An experimental test of this hypothesis is reported below.

The strategies examined in the simulations differed in several ways, e.g., amount of information processed, selectivity in processing, and form of processing. For example, the Weighted Additive (WADD) process involves no selectivity in processing. The values of each alternative on all the relevant attributes and all the relative importances (weights) of the attributes are considered. The WADD strategy also uses alternative-based processing: all information about the multiple attribute values of a single alternative is processed before information about a second alternative is considered. In contrast, elimination-by-aspects (EBA) selectively attends to a subset of the

available information. The processing of information is also attribute-based. That is, information about the values of several alternatives on a single attribute is processed before information about a second attribute is processed. When the results of the simulation are presented in Table 1 below, the form of processing and selectivity are indicated for each rule as an aid in interpreting those results.

Measuring Accuracy

Accuracy of choice could be defined by basic principles of coherence, such as avoiding selection of dominated alternatives or intransitive patterns of preferences. However, more specific criteria for choice accuracy can be developed in certain types of task environments. For instance, the expected utility (EU) model is generally suggested as a normative decision procedure for risky choice because it can be derived from more basic principles. A special case of the EU model, the maximization of expected value (EV), has been used as a criterion to investigate the accuracy of decision heuristics via computer simulation (Thorngate, 1980). A similar model, the weighted additive rule, is often used as a criterion for decision effectiveness in multiattribute choice (Zakay & Wooler, 1984).

In our research, we have emphasized a measure of accuracy that considers the performance of a heuristic relative to the upper and lower baseline strategies of (1) maximization of Expected Value (or the equivalent Weighted Additive Value) and (2) random choice. The accuracy measure provides an indication of the relative performance of heuristics:

$$\text{Relative Accuracy} = \frac{EV_{\text{heuristic rule choice}} - EV_{\text{random rule choice}}}{EV_{\text{expected value choice}} - EV_{\text{random rule choice}}}$$

This measure is bounded by a value of 1.0 for the expected value rule and an average value of 0.0 for the random rule. While we have relied primarily on this

measure of relative accuracy, we have used other measures with similar results (Johnson and Payne, 1985). Note, incidentally, that an Expected Value strategy represents a complete use of the information in the problem statement. A random choice rule, in contrast, uses none of the information.

Task and Context Environments

Several aspects of choice tasks were investigated in the simulations, including number of alternatives, number of attributes (outcomes), time pressure, dispersion of probabilities within each gamble, and the possibility or absence of dominated alternatives. Task size (i.e., the number of alternatives and the number of attributes) was included in the simulation because variations in choice problem size have produced some of the clearest examples of contingent decision behavior (Payne, 1982). Time pressure was of particular interest, since the use of a normative decision strategy like expected value maximization may be less attractive or infeasible under time constraints (Simon, 1981). Under time pressure, deciding how to choose becomes a selection of the "best" of the available heuristics, not a choice between using some heuristic or the optimal normative rule. To illustrate the dispersion of probabilities variable, a four outcome gamble with a low degree of dispersion might have probabilities of .30, .20, .22, and .28 for the four outcomes. In contrast, a gamble with a high degree of dispersion might have probabilities such as .68, .12, .05, and .15. This variable was included because Thorngate (1980) had suggested that probability information may be relatively unimportant in making accurate risky choices (see also Beach, 1983). Finally, the absence or possibility of dominated alternatives was included because McClelland (1978), among others, has suggested that the use of certain simplification procedures, such as the equal weighting strategy, is dependent upon the presence of dominated alternatives.

Time constraints, number of alternatives, and number of attributes represent *task variables*, which are variables associated with general characteristics of the decision problem and not dependent on the particular values of the alternatives. Dominance possible or absent and dispersion of probabilities, on the other hand, represent *context variables*, which are variables associated with the particular values of the alternatives (Payne, 1982).

Results

Table 1 summarizes the results of our simulations for the two context variables and the two extreme time pressure conditions (absent and severe). These results support four major conclusions. First, the simulations show that heuristics, in at least some task environments, can approximate the accuracy of normative rules with substantial savings in effort. For example, in an environment characterized by high dispersion in probabilities, dominance possible, and no time constraint, the lexicographic strategy achieved a 90% relative accuracy score, with only about 40 percent of the effort that would be needed to use a normative strategy like EV (i.e., 60 as opposed to 160 EIPs).

 Table 1 about here

Second, no single heuristic did well across all decision environments. For instance, in the no time pressure condition, when the dispersion in probabilities varied from high to low, the accuracy of the lexicographic rule dropped from 90% to 69%. In contrast, the alternative simplification represented by the equal weighting strategy produced an increase in accuracy from 67% to 89% as dispersion in probabilities went from high to low. The existence of efficient heuristics and the sensitivity of heuristics to changes in task environments are highlighted by Figure 1, which shows the relative effort and accuracy associated with

Table 1
Simulation Results for Accuracy and Effort of Heuristics

Strategy	form	Processing selectivity	Time Pressure Absent						Severe Time Pressure					
			Dominance possible			Dominance not possible			Dominance possible			Dominance not possible		
			Low	High	dispersion	Low	High	dispersion	Low	High	dispersion	Low	High	dispersion
WADD	Alternative	No	1.0	1.0	1.0	1.0	1.0	1.0	.28	.28	.12	.24	NA	
RA			160	160		160			NA	NA		NA		
UOC														
EQW	Alternative	No	.89	.67	.41	.85	.27	.72	.55	.26	.18	NA		
RA			85	85			85		NA	NA		NA		
UOC														
LEX	Attribute	Yes	.69	.90	.67	.60	.90	.47	.59	.48	.60	NA		
RA			60	60			60		NA	NA		NA		
UOC														
LEXSEM1	Attribute	Yes	.71	.87	.64	.79	.77	.40	.49	.43	.51	NA		
RA			87	78			81		NA	NA		NA		
UOC														
EBA	Attribute	Yes	.67	.66	.54	.82	.56	.49	.65	.48	.61	NA		
RA			87	88			82		NA	NA		NA		
UOC														
SAT	Alternative	Yes	.32	.31	.03	.61	.07	.30	.23	.06	.04	NA		
RA			49	49			61		NA	NA		NA		
UOC														
MCD	Attribute	No	.62	.48	.07	.141	.09	.23	.17	.02	.02	NA		
RA			148	148			140		NA	NA		NA		
UOC														
EBA+WADD	Mixed	Yes	.84	.79	.69	.102	.66	.43	.48	.27	.43	NA		
RA			104	106			102		NA	NA		NA		
UOC														
EBA+MCD	Attribute	Yes	.69	.59	.29	.86	.31	.44	.49	.27	.36	NA		
RA			89	89			86		NA	NA		NA		
UOC														

Note: RA = relative accuracy (95% confidence interval width = $\pm .029$). UOC = unweighted operations count (95% confidence interval width = ± 2.75). WADD = weighted additive strategy. EQW = equal weight strategy. LEX = lexicographic strategy. LEXSEM1 = lexicographic semi-order strategy. EBA = elimination by aspects strategy. SAT = satisficing strategy. MCD = majority of confirming dimensions strategy. EBA+WADD = combined elimination by aspects plus weighted additive strategy. EBA+MCD = combined elimination by aspects plus majority of confirming dimensions strategy. The UOC is marked NA in the severe time pressure conditions because the operations count was constrained to be approximately 50 for all rules in these conditions.

different strategies in two different environments. One prediction that can be drawn from Figure 1 concerns the relative effort and accuracy of the equal weight and lexicographic strategies as a function of dispersion in probabilities. Note that for the equal weight strategy in a low dispersion environment and the lexicographic strategy under high dispersion, the accuracy obtained is roughly equal. However, less effort is required in the high dispersion condition. Thus, a decision maker desiring relatively high levels of accuracy could maintain that accuracy across contexts through a shift in strategies, but with a substantial savings in effort in the high dispersion environment. More generally, Figure 1 and other results reported in Johnson and Payne (1985) and Payne et. al. (1988) suggest that in order to achieve both a reasonably high level of accuracy and low effort, a decision maker would have to use a repertoire of strategies, with strategy selection contingent upon situational demands.

 Figure 1 about here

A third conclusion was that both the effort and accuracy of strategies were differentially affected by number of alternatives, number of attributes, and the possibility or absence of dominance. For example, the effort required to use heuristics such as EBA increased much more slowly than the effort required to use the weighted additive rule as the number of alternatives increased. This simulation result is compatible with substantial empirical research showing strategy shifts due to the number of alternatives (Payne, 1982). The decision task characterized by dominance absent and low dispersion in probabilities was one in which no heuristic did particularly well in terms of accuracy. The accuracy score of the best simple heuristic, LEX, was only .67, or .22 less than the accuracy score for the "best" heuristic in the other environments. Since a

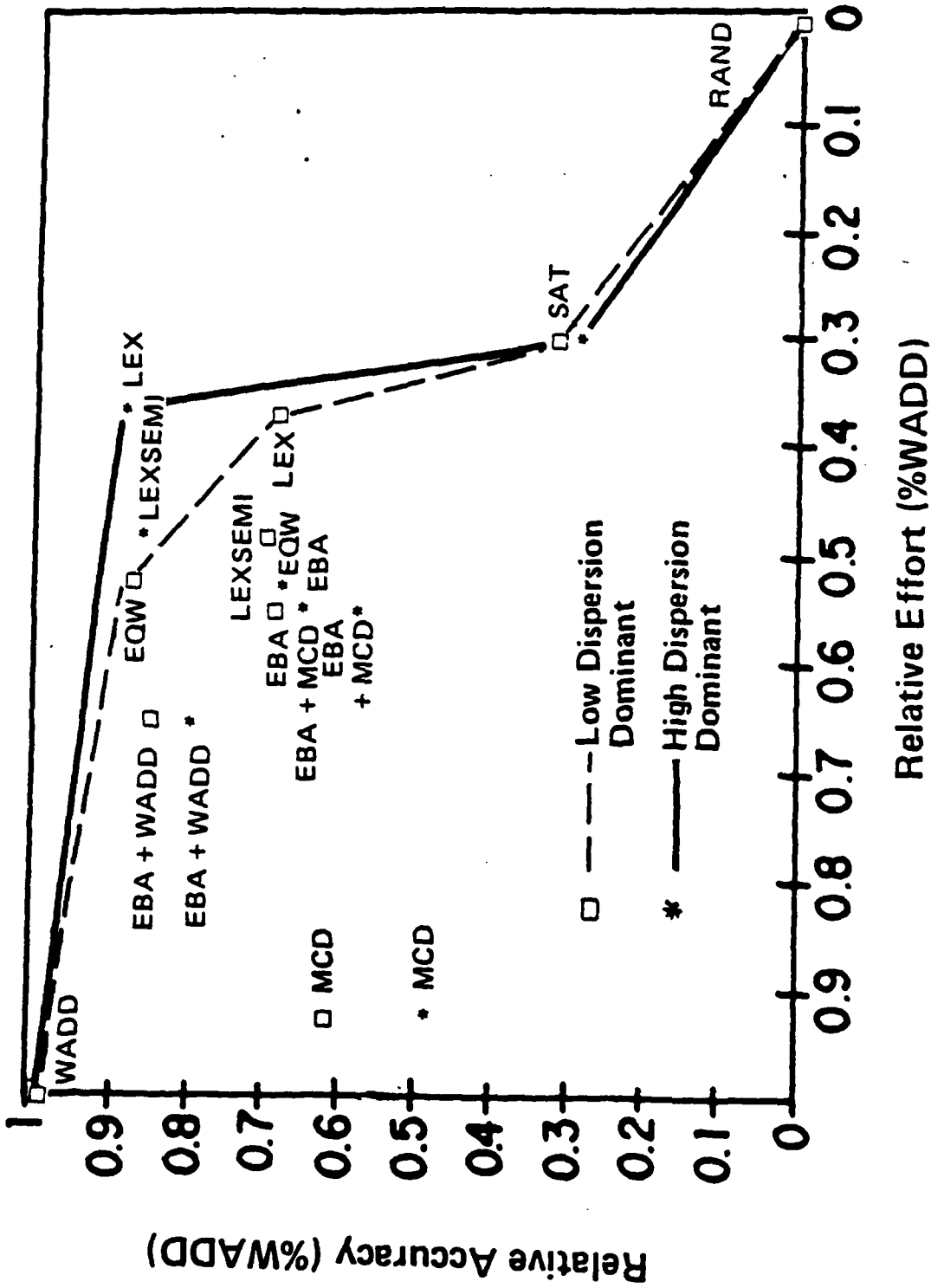


Figure 1. Effort/Accuracy tradeoffs for various decision strategies in the low-dispersion (\square) and high-dispersion ($*$) environments where dominance is possible. The lines join the most efficient pure strategies for each environment.

decision maker would not be able to reduce effort appreciably without suffering a substantial loss in accuracy in this type of task environment, such an environment should be perceived as particularly difficult. In fact, when asked, subjects report that decisions in the dominance absent, low dispersion choice environments are more difficult. Subjects also take longer to make decisions in this environment than in the other three environments representing combinations of dominance possible or absent and dispersion.

Fourth, time constraints were shown to have differential effects on the various decision strategies. The weighted additive rule, for example, showed a reduction in accuracy from the baseline value of 1.0 under no time pressure to an average accuracy of only .12 under the most severe time constraint in the dominance absent-low dispersion environment. Strategies which require many EIPs show degraded performance under time pressure because such procedures must be truncated when time runs out.² In contrast, the EBA heuristic was relatively unaffected by time pressure. The average accuracy across environments was only reduced from .69 under no time pressure to .56 with severe time pressure. More generally, under high time pressure, strategies that process at least some information about all alternatives as soon as possible performed best.

The simulation results indicated what a decision maker could do to adapt to various decision environments. The results clearly suggested that a decision maker could maintain a high level of accuracy and minimize effort by using a diverse set of heuristics, changing rules as context and task characteristics change.

Note, however, that the simulation results alone do not identify which particular strategy a decision maker will select in a given decision task. That would depend on the degree to which a decision maker was willing to trade decreases in accuracy for savings in effort. This tradeoff might depend on

factors such as the decision maker's goal structure, the size of the payoffs, and the need to justify a decision. We will discuss the role of such factors in strategy selection in more detail below, but it is important to recognize that the simulation indicates general changes in processing that might be expected regardless of any particular trade-off between effort and accuracy, e.g., the effect of dispersion on the attractiveness of a lexicographic versus equal-weight strategy.

Thus, the results of the simulation yield interesting predictions about the general patterns of processing which might characterize decision makers desiring to make efficient accuracy/effort tradeoffs. However, the simulation work itself would remain only suggestive without further validation. For example, the simulation makes the crucial assumption that EIP counts represent reasonable measures of effort. Both this assumption and the predicted patterns of processing can be examined experimentally with actual decision makers. The next two sections report this empirical work.

Cognitive Effort in Choice

The research reported in this section examined the assumption that EIP counts provide a measure of cognitive effort. Decision makers made choices using different prescribed strategies for choice sets varying in size. Both decision latencies and self-reports of decision difficulty were obtained as measures of strategy execution effort. The crucial question was whether models based on EIP counts could predict these two indicators of cognitive effort in choice. In addition, we characterized how the effort required by subjects to use different decision strategies varied as task size (number of alternatives and number of attributes) varied. Given space constraints, the following description of our methods and results is necessarily limited; see Bettman, Johnson, and Payne (In press) for more details.

Overview of method

Seven subjects were trained to use six different decision strategies: weighted additive, equal weighting, lexicographic, elimination-by-aspects, satisficing, and majority of confirming dimensions. Each strategy was used by each subject in a separate session to make twenty decisions ranging in problem size from two to six alternatives and from two to four attributes. The decision problems involved selection among job candidates. For each session, subjects were to use the prescribed rule exactly as given to them to make their selections. Subjects used the Mouselab computer-based information acquisition system to acquire information and make their decisions (Johnson, Payne, Schkade, and Bettman, 1988). Subjects used a mouse as a pointing device to move a cursor around a screen containing the probabilities and outcome values in a matrix format. When the cursor pointed to a cell of the matrix, the information in that cell was displayed and all other information remained concealed. The computer-based acquisition system monitored the subjects' information sequences and recorded latencies for each acquisition, the overall time for each problem, any errors made by the subject (i.e., departures from the prescribed search pattern or choice), and the choice. In addition, subjects rated the difficulty of each choice and the effort each choice required on two response scales presented at the end of each decision problem. Subjects also provided data in a seventh session for twelve choice problems of various sizes where the subject was free to use any strategy desired.

Results

As expected, decision problems of increasing complexity, i.e., more alternatives and/or more attributes, took longer and were viewed as more effortful. Of greater interest, the effects of task complexity varied by strategy. Compared to other strategies, the weighted additive rule (WADD) showed

much more rapid increases in response time and somewhat more rapid increases in self-reports of effort as a function of increased task complexity. Thus, there was evidence of a strategy by task interaction in terms of these two indicators of cognitive effort.

The central question of interest, however, was whether the EIP framework could predict the effort required by each strategy in the various task environments. To answer this question, we used regression analyses to assess the degree to which four alternative models of effort based on EIPs fit the observed response times and self-reports of effort. The simplest model treated each EIP as equally effortful and summed the numbers of each component EIP to get an overall measure of effort (the equal-weighted EIP model). The second model allowed the effort required by each individual EIP to vary (the weighted EIP model) by using counts for each of the individual EIPs as separate independent variables. A third model allowed the effortfulness of the individual EIPs to vary across rules (the weighted EIP by rule model). While such a variation is possible, of course, the goal of developing a unifying framework for describing the effort of decision strategies would be much more difficult if the sequence of operations or the rule used affected the effort required for individual EIPs. The fourth model allowed the required effort for each EIP to vary across individuals, but not rules (the weighted EIP by individual model), based on the expectation that some individuals would find certain EIPs relatively more effortful than other individuals. A fifth model based simply on the amount of information processed (the information acquisitions model) was also assessed as a baseline model of decision effort. This last model implies that the specific type of processing done on the information acquired makes little or no difference in determining decision effort.

Overall, the results yielded strong support for the EIP approach to strategy effort. A model of effort based upon weighted EIP counts provided good fits for response times ($R^2 = .84$) and self-reports of effort ($R^2 = .59$). In addition, the fit of the weighted EIP model to the data was statistically superior to the baseline model of information acquisitions and to the equal-weighted EIP model. Thus, it appears that a model of cognitive effort in choice requires not only concern for the amount of information processed, but also differential weighting of the particular processes (EIPs) applied to that information. Interestingly, the estimates of the time taken for each EIP were mostly in line with prior cognitive research. For example, the READ EIP combines encoding information with the motor activity of moving the mouse. Its estimated latency is 1.19 seconds. This estimate is plausible, since it might consist of the movement of the mouse, estimated to be in the range of .2 - .8 seconds by Johnson, Payne, Schkade, and Bettman (1988), and an eye fixation, estimated to require a minimum of .2 seconds (Russo, 1978). ADDITIONS and SUBTRACTIONS both take less than one second, with estimates of .84 and .32, respectively. These values are not significantly different and are consistent with those provided by Dansereau (1969), Groen and Parkman (1972), and others (see Chase, 1978, Table 3, p. 76). Our estimate for the PRODUCT EIP, 2.23 seconds, is larger than that commonly reported in the literature. The time for COMPARES is very short, .08 seconds, and that for ELIMINATIONS, 1.80 seconds, is relatively long. This may reflect the collinearity of COMPARES and ELIMINATIONS.

The weights for the various EIPs were essentially the same regardless of the decision strategy used. That is, the fits for the more complex weighted EIP by rule model were essentially the same as the fits for the weighted EIP model. This supports the assumption of independence of EIPs across rules.

However, the results showed significant individual differences in the effort associated with individual EIPs, suggesting that individuals may choose different decision strategies in part because component EIPs may be relatively more or less effortful across individuals. In fact, Bettman, Johnson, and Payne (In press) show that the processing patterns used by subjects in an unconstrained choice environment were related to the relative costs of certain EIPs, although the limited number of subjects in that study precluded any strong conclusions. Subjects for whom arithmetic operators were relatively more difficult, as indicated by the coefficients for the various EIPs, showed greater selectivity in processing.

To summarize, we found strong support for the EIP approach to conceptualizing and measuring the effort of executing a particular choice strategy in a specific task environment. Next, we examine whether the general patterns of processing predicted by the simulation agree with the processing patterns exhibited by decision makers adapting to variations in dispersion of probabilities and time pressure. Such a match, together with the success of the EIP approach to measuring effort reported above, would provide powerful support for our proposed approach to contingent strategy selection. In the next section, therefore, we consider adaptivity in strategy selection when both effort and accuracy may be valued and when subjects are free to use any information processing strategy they wish in making a choice.

Adaptive Strategy Selection

The experiments asked the following two questions: (1) To what extent do people vary their information processing behavior as a function of context effects such as the dispersion of probabilities and task effects such as time pressure?; and (2) Are these changes in processing in the directions suggested by

the simulation work described earlier? Again, the method and results can only be summarized. Details can be found in Payne, Bettman, and Johnson (1988).

Method

Two experiments were conducted in which subjects were asked to make a series of choices from sets of risky options. Each choice set contained four risky options, with each option offering four possible outcomes (attributes). For any given outcome, the probability was the same for all four options. Thus, there was only one set of probabilities for each set of four alternatives. The payoffs ranged from \$.01 to \$9.99. Dominated options were possible. At the end of an experiment, subjects actually played one gamble and received the amount of money that they won. The sets varied in terms of two factors: (1) presence or absence of time pressure and (2) high or low dispersion in probabilities. In terms of the simulation, the no time pressure conditions correspond to the dominance possible, low and high dispersion conditions shown in Figure 1. The high time pressure sets correspond to conditions not shown in Figure 1, but the general patterns of results for such conditions were briefly discussed in the section describing the simulation results. In the first experiment, the time pressure condition involved a 15 second time constraint. In the second experiment, half the subjects had a 15 second constraint. The other half had a more moderate 25 second time constraint. Also, in the second experiment subjects returned for a second experimental session that was similar to the first except that the time constraint was at the level they had not yet experienced, i.e., the time pressure for the second session was set at 25 seconds if the subject was in the 15 second condition on the first day and vice versa. For comparison, the average response time for the no time pressure conditions was 44 seconds.

The design was a complete within-subjects procedure, with a total of 40 randomly ordered decision problems in an experimental session, ten in each of the

four dispersion by time pressure conditions. This design was motivated by the desire to provide the strongest possible test of adaptivity in decision making (i.e., the same subject would be expected to switch strategies from one trial to the next). The subjects were not provided any accuracy feedback in these experiments for two reasons: (1) It is the exception, rather than the rule, for probabilistic decision problems to provide immediate and clear outcome feedback (Einhorn, 1980); (2) To the extent that adaptivity is exhibited in such situations, it suggests that adaptivity is crucial enough to decision makers that they will guide themselves to it without the need for explicit feedback.

Information acquisitions, response times, and choices were monitored using the Mouselab system (Johnson et. al., 1988). For the time constrained trials, the Mouselab system ensured that subjects could not collect any additional information once the available time had expired. A clock on the display screen was used to indicate the time left as it counted down.

Results

Overall, the results for subjects' actual decision behaviors validated the patterns predicted by the simulation. Subjects showed a substantial degree of adaptivity in decision making, although this adaptivity was not perfect.

More specifically, subjects processed less information, were more selective in processing, and tended to process more by attribute when dispersion in probabilities was high rather than low. Moreover, accuracy was equivalent for the two dispersion conditions. Thus, subjects showed an ability to take advantage of changes in the structure of the available alternatives so as to reduce processing load while maintaining accuracy. Recall that this prediction was drawn from the simulation results.

At the level of individual subject behavior, there was evidence that subjects who were more adaptive in their patterns of processing (i.e., relatively

more selective and attribute-based processors in high dispersion environments) also performed better in terms of relative accuracy scores. Importantly, this increase in performance was not accompanied by a significant increase in effort. Hence, more adaptive subjects also appeared to be more efficient decision makers.

Several effects of time pressure were also demonstrated. First, under severe time pressure, people accelerated their processing (i.e., less time was spent per item of information acquired), selectively focused on a subset of the more important information, and changed their pattern of processing in the direction of relatively more attribute-based processing. This general pattern of results is consistent with the simulation, which suggested that an efficient strategy under severe time pressure was one that involved selective and attribute-based processing.

The effects of time pressure were substantially less for those subjects with a 25 as opposed to 15 second constraint. In the more moderate condition, subjects showed evidence of acceleration in processing and some selectivity in processing, but no evidence of a shift in the pattern of processing. These results suggested a possible hierarchy of responses to time pressure. First, people may try to respond to time pressure simply by working faster. If this is insufficient, people may then focus on a subset of the available information. Finally, if that is still insufficient, people may change processing strategies, e.g., from alternative-based processing to attribute-based processing.

Although these results suggest high adaptivity, there was evidence to suggest that the adaptivity to time pressure was not perfect on a trial by trial basis. When the responses to the no time pressure condition were compared for the two groups of subjects in the second experiment, some carryover from behavior generated in response to the time pressure trials to performance on the no time pressure trials was detected. Specifically, subjects who had the more severe 15

second time constraint showed comparatively more attribute-based processing, even in the no time pressure trials.

To summarize, the results provided strong evidence of adaptivity in decision making. While not perfectly adaptive, our subjects were able to change processing strategies in ways that the simulation indicated were appropriate. Taken together, the results of the simulation, models of cognitive effort, and experiments in adaptive decision making provide strong and consistent support for the proposed EIP approach to strategy selection. We believe that this approach provides a more systematic approach to characterizing effort and accuracy for decision strategies than any other currently available. It is our belief that further application of this conceptualization to problems of contingent strategy selection would be very fruitful.

Although we are excited by the progress made thus far, there are several incomplete aspects of our framework. The next section examines several of these issues.

Some Unresolved Issues

Implicit in our approach is a top-down view of strategy selection. When deciding how to decide, a decision maker is assumed to evaluate the costs and benefits of the various strategies known to him or her and to select that strategy which is in some sense best for the environment. We now believe that this view is too restrictive. While we still espouse an effort/accuracy viewpoint and the idea of multiple strategy use, we have begun to consider several broader concerns which lead to a more complex view of contingent decision behavior.

Assessing How Well One is Doing

In order to adapt to task demands, it seems reasonable that individuals must determine, even if roughly, how well they are doing. The notion of adjustment

via effort/accuracy tradeoffs, in particular, implies the ability to generate ideas about the degree of effort and accuracy characterizing one's decision process. Our data on adaptivity in strategy use suggest that people can learn to change behavior as a function of task and context variables. Yet none of the experiments provided subjects with explicit accuracy or outcome feedback. Thus, how do people learn when and how to change decision strategies?

In the absence of explicit feedback, individuals must somehow generate their own feedback about effort and accuracy. This is not too difficult to imagine for effort. In the course of solving a decision problem, the decision maker has a fairly rich data base available about how effortful and/or difficult he or she is finding the decision. This *process feedback* (Anzai and Simon, 1979) could provide the basis for a change in strategy. To illustrate, consider a faculty member asked to identify a small number (3) of job candidates to be brought in for an interview. Assume that over 100 applications have been received. Also assume that the faculty member is inexperienced at this task and that he or she wants to do a good job. Initially, we suspect that the faculty member would try to evaluate each application in great depth. However, at some point that person would likely recognize that the process is becoming increasingly effortful and would think about a change in processing strategy. One implication of such readily available process feedback on effort is that considerations of effort will play a prominent role in strategy selection.

Self-generation of accuracy feedback is not as obvious. One possibility is that along with process feedback, people have some general knowledge of the properties of a reasonable strategy. For example, decision makers might believe that a good strategy involves looking first at the most important information for all alternatives, and then looking at other information as desired or as time allows. Some data supporting such general beliefs about good decision strategies

are reported in Payne et. al. (1988). With such knowledge, the individual could not only ascertain the effort required during the course of making a decision, but could also determine how closely this decision process resembled his or her notion of what a "good" strategy should entail. In the absence of environmental constraints, the match between the strategy used and notions of a "good" strategy should presumably be close and the individual's accuracy assessment would be "high". However, if there were severe environmental constraints (e.g., great time pressure), the individual may feel that the strategy, either as executed or while executing, did not match his or her notion of a reasonable strategy. For example, important information may not have been examined before time ran out. Klein (1983) reports data supporting this kind of learning about the task during decision making. The individual could then adjust the decision process to be more in line with his or her notion of reasonableness, either on-line or the next time such a decision was faced.

Recently, Reder (1987) has considered strategy changes without explicit feedback in a task dealing with question answering strategies and proposed a "feeling of knowing" process that is related to our ideas. She argues that people may develop strategies that are adaptive to different problem environments by trying to minimize effort while maintaining a feeling of knowing that a reasonable answer is being produced. An interesting issue is how well-calibrated such feelings of knowing may be in the area of decision making, and how they are affected by decision task properties.

The possibility that process feedback provides information about both the effort and accuracy of making a decision raises another question: Under what conditions will explicit feedback about effort and accuracy be used by decision makers? Creyer, Bettman, and Payne (1988) found that explicit feedback on the time used to make a decision (a measure of effort used) had no effect on decision

processes. Of greater interest, explicit accuracy feedback also had little impact for decision problems similar to the high dispersion in probabilities (weights) choice problems used in Payne et. al. (1988) and discussed above. On the other hand, explicit accuracy feedback did change processing and improve performance for those decision problems involving low dispersion in weights (probabilities). One explanation of these results is that explicit accuracy feedback is only needed to supplement process feedback for those situations where the decision maker is faced with more difficult problems. When asked to rate decision problems according to degree of difficulty, subjects rated low dispersion problems as more difficult than high dispersion problems.

Although there is a large literature on feedback, learning, and judgment (Brehmer, 1980; Einhorn, 1980), issues regarding learning and contingent strategy selection in decision making are just beginning to be explored. However, a better understanding of the role of process feedback and strategy selection seems crucial for building a more complete model of the adaptive use of heuristics in decision making. As discussed in Johnson and Payne (1985), learning mechanisms in decision making also offer a solution to the infinite regress difficulty associated with the hypothesis that people decide how to choose. Such strategy decisions are not made often, but the relationship between task and context variables and the efficiency of a decision strategy is learned over time. Finally, as discussed next, process feedback may also be important in understanding the construction of decision processes (Bettman, 1979) as well as their selection.

A Constructive View of Choice and Editing

As noted above, effort/accuracy frameworks for strategy selection often implicitly assume a top-down process. That is, information about the task is used to assess the costs and benefits of various strategies, and the best

strategy is then selected and applied to solving the choice problem. There are data supporting such a goal-directed process of strategy selection (Payne, 1976). Nonetheless, heuristic problem solvers not only use information extracted from the initial problem definition in deciding how to search, but also utilize information from states already explored in the problem space to identify promising paths for search (Langley, Simon, Bradshaw, and Zytkow, 1987). That is, as people learn about the problem structure during the course of making a decision, they may change their processing to exploit this structure. This view of strategy selection as an opportunistic process (Hayes-Roth and Hayes-Roth, 1979) also suggests that editing processes (Kahneman and Tversky, 1979) are a crucial component of adaptivity.

Editing processes have been proposed as an important component of choice (Kahneman and Tversky, 1979; Goldstein and Einhorn, 1987), with individuals supposedly editing choice problems into simpler forms before choosing. Editing could involve cancellation of outcomes which are identical across alternatives, eliminating dominated alternatives, and/or combining of equal payoff outcomes, for example. To the extent that editing can simplify choice, it is potentially a major component in understanding the role of cognitive effort and adaptivity to different decision environments.

Whereas Kahneman and Tversky (1979) and Goldstein and Einhorn (1987) argue that editing processes come first, with alternatives edited and then the simplified options evaluated, we argue instead that editing occurs throughout a choice whenever individuals notice some structure in the choice environment that can be exploited. Hence, editing can be a bottom-up process, driven by the data, as well as a priori or top-down. Thus, one might not decide a priori to eliminate dominated alternatives but might eliminate such alternatives only if noticed during the course of processing.

The editing process itself may be adaptive in that the particular editing operations used may be a function of problem states already explored. Different types of processing will leave different traces in working memory, and these traces will be more or less compatible with different editing operations. For example, processing a pair of alternatives using an attribute-based form of processing will facilitate the detection of dominance, whereas an alternative-based form of processing would discourage such detection. Hence, different choice strategies enable different editing operations during the course of processing. Therefore, different choice environment properties will affect editing because they affect strategy selection. This is likely to be particularly true for the effects of information display. Slovic, for example, (1972) has argued for a principle of concreteness, which states that individuals tend to use information in the form in which it is displayed. To the extent this is true, display should exert a strong influence on editing processes by encouraging or discouraging various types of processing.

This opportunistic view of editing implies a more constructive view of choice (Bettman, 1979). Such a view implies that people develop simplifications and strategies as they progress in a decision process, rather than invoking them a priori. Which regularities in the task environment (if any) are noted and exploited can profoundly affect the course of the decision process, so the sequence of editing operations can have a major impact on the resultant process and decision (Tversky and Kahneman, 1986).

Amazingly, however, almost nothing is known about editing processes. Such research topics as what features of a decision task are noticed and exploited, how this changes with display format, and studies of the determinants of focus of attention in decision making are badly needed. We agree with Yates, Jagacinski, and Faber (1978) that events affecting attention in the real world are likely to

be numerous and powerful and that such events are not just experimental nuisance factors.

Incentives and Strategy Selection

As stated at the beginning of this chapter, the major focus of our research has been on the role of cognitive effort in strategy selection. Questions of strategy accuracy have played an important, but secondary, role in our research. In particular, we have not emphasized the direct role of incentives in strategy selection, although subjects in our studies do receive compensation tied to performance. However, it is clear that an effort/accuracy framework for strategy selection must deal with incentive effects more directly.

The effort/accuracy framework implies that people should utilize strategies that provide greater accuracy at the cost of greater effort when the incentives associated with accuracy are increased. However, as pointed out by several authors (Tversky and Kahneman, 1986; Wright and Aboul-Ezz, 1986), incentives sometimes enhance performance and at other times have no effect. We have obtained similar mixed results in our own research. Sometimes incentive effects are in the direction predicted by our framework, in that people increase the amount of processing, are less selective in processing, and process more by alternative than by attribute when goals and incentives are structured to emphasize accuracy more than effort (Creyer, Bettman, and Payne, 1988). At other times, however, we have found incentive effects either difficult to detect or in directions opposite from those predicted. For example, Simonson (1987) found that the frequency with which the context variable of asymmetric dominance relationships (Huber, Payne, and Puto, 1982) impacts choice is increased with an increased need to justify one's decision. To the extent that the need to justify or be accountable for a decision impacts on the desire to make a "good" decision

(Beach and Mitchell, 1978; Tetlock, 1985), this finding seems contrary to what one would expect.

One solution to the ambiguity of this research is the common distinction between working harder versus working smarter. Tversky and Kahneman (1986), for example, argue that incentives work by focusing attention and prolonging deliberation. That is, incentives cause people to work harder but not necessarily smarter (see also Einhorn & Hogarth, 1986). However, if people do not change strategies but just work harder, this may have the paradoxical effect of increasing error in decisions through increased effort applied to executing a flawed strategy (Arkes, Dawes, and Christensen, 1986). It is also important to recognize that incentives will not eliminate errors if a normative strategy is impossible to use due to information processing limitations or environmental factors such as severe time pressure (Simon, 1981). Finally, any shift in strategy due to incentives would seem to require awareness of alternative strategies. In some cases, incentives may have limited impact due to a lack of awareness of any better decision strategy than the one currently being used. Thus, one important direction for research on strategy selection is to understand better when and how incentives will impact processing and choice.

To this point, we have reviewed research concerned with basic research questions in the area of behavioral decision research. However, as indicated in the theme of this conference, the work of Hillel Einhorn was concerned both with theory and application. Consequently, we will end this chapter with a discussion of one implication of our program of research for improving decisions.

Designing Decision Displays

An exciting application of the effort/accuracy approach is guiding the design of information displays to facilitate better decision making. By designing displays which make more effective processing easier, decision

performance should be improved. Like Slovic (1972), we suspect that decision-makers are greatly influenced by the form of the information presented and are unlikely to transform information so that it will fit strategies. By making better strategies easier to use, the application of more efficient decision heuristics can be encouraged.

An excellent demonstration of decision aiding through information display changes is provided by Russo (1977). Russo argued that using unit price information in the supermarket was unduly effortful, requiring that consumers locate the various unit-price tags spread throughout the shelf and remember these values until other brands could be located. He reduced the required effort by combining all unit-price tags into a single list, sorted by unit price. A field study comparing the existing shelf tags and the list showed that the list produced a 2% decrease in the average price paid, representing 11% of the savings possible by always buying the least expensive brand. More generally, encouraging the use of efficient strategies by making them easier to execute has important implications for providing product information to the public (Bettman, Payne, and Staelin, 1986).

Johnson, Payne, and Bettman (1988) show that the design of information displays can have important consequences on the frequency of one of the most dramatic decision errors, the preference reversal (Lichtenstein and Slovic, 1971). In the preference reversal paradigm, subjects choose among and give monetary equivalents for two gambles. Preference reversals occur when a subject indicates a choice of one gamble but gives a higher monetary equivalent for the other gamble in the pair. In the typical preference reversal experiment, the probabilities are described as fractions, a consequence of using a roulette wheel to determine outcomes. Johnson et al. suggested that these fractions (29/36, for example) discouraged the use of expectation strategies and facilitated the use of

heuristic strategies which produced reversals. They manipulated the way identical probabilities were displayed, ranging from simple decimals (.8) to quite complex fractions (284/355). The complex fractions produced almost twice as many reversals as the decimals. Further, process-tracing measures, collected with Mouselab, were consistent with the notion that the simpler displays encouraged using expectation strategies.

Together, these examples illustrate the principle of passive decision support. In contrast to more active approaches which replace human cognitive processes to aid decisions, better decisions can be encouraged by designing displays which passively encourage more accurate strategies by making them easier to execute. Such reductions in execution effort can be achieved by using formats which make operations such as comparisons easier or by making individual pieces of data easier to process, for example.

Conclusion

A major finding of the last twenty years of decision research is that an individual will use many different strategies in making a decision, contingent upon task demands (Einhorn and Hogarth, 1981; Payne, 1982; Abelson and Levi, 1985). The use of multiple strategies raises the fundamental issue of how people decide to decide. This chapter reviews a program of research directed at understanding the adaptive use of strategies in decision making. While people clearly sometimes make decisions that violate certain principles of rationality (Tversky, 1969), it is also becoming clear that decision makers often adapt in directions representing efficient effort/accuracy tradeoffs.

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Footnotes

1. Different EIPs may require different levels of effort. For example, comparing two values may be easier than adding or multiplying them. Hence, the operator counts could be weighted by some measure of the effort required for each individual operator, such as the time estimates mentioned below. The results remain essentially the same whether a weighted or unweighted EIP count is used to measure effort.
2. Depending upon the definition of the particular strategy, the alternative selected when time ran out was either the best alternative processed up to the point time ran out or an alternative randomly chosen from those alternatives not yet eliminated when time ran out.

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